



# Conceptualizing a probabilistic risk and loss assessment framework for wildfires

Negar Elhami-Khorasani<sup>1</sup> · Hamed Ebrahimian<sup>2</sup> · Lawrence Buja<sup>3</sup> · Susan L. Cutter<sup>4</sup> · Branko Kosovic<sup>5</sup> · Neil Lareau<sup>2</sup> · Brian J. Meacham<sup>6</sup> · Eric Rowell<sup>7</sup> · Ertugrul Taciroglu<sup>8</sup> · Matthew P. Thompson<sup>9</sup> · Adam C. Watts<sup>10</sup>

Received: 17 January 2022 / Accepted: 23 June 2022  
© The Author(s), under exclusive licence to Springer Nature B.V. 2022

## Abstract

Wildfires are an essential part of a healthy ecosystem, yet the expansion of the wildland-urban interface, combined with climatic changes and other anthropogenic activities, have led to the rise of wildfire hazards in the past few decades. Managing future wildfires and their multi-dimensional impacts requires moving from traditional reactive response to deploying proactive policies, strategies, and interventional programs to reduce wildfire risk to wildland-urban interface communities. Existing risk assessment frameworks lack a unified analytical method that properly captures uncertainties and the impact of decisions across social, ecological, and technical systems, hindering effective decision-making related to risk reduction investments. In this paper, a conceptual probabilistic wildfire risk assessment framework that propagates modeling uncertainties is presented. The framework characterizes the dynamic risk through spatial probability density functions of loss, where loss can include different decision variables, such as physical, social, economic, environmental, and health impacts, depending on the stakeholder needs and jurisdiction. The proposed approach consists of a computational framework to propagate and integrate uncertainties in the fire scenarios, propagation of fire in the wildland and urban areas, damage, and loss analyses. Elements of this framework that require further research are identified, and the complexity in characterizing wildfire losses and the need for an analytical-deliberative process to include the perspectives of the spectrum of stakeholders are discussed.

**Keywords** Wildfire · Damage · Loss · Spatial probability density function · Performance-based approach

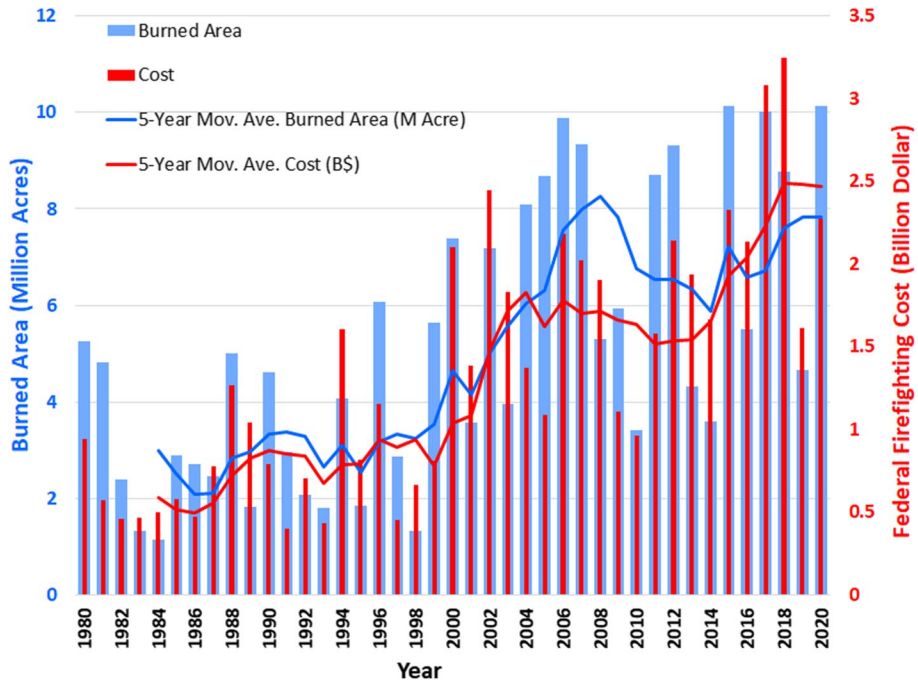
## 1 Introduction

The US faces a serious threat from wildland fires. Aggravated by anthropogenic activities and climate change (e.g., Abatzoglou and Williams 2016; Littell et al. 2009), wildland fire is rapidly becoming one of the most significant natural hazards threatening the physical,

---

✉ Negar Elhami-Khorasani  
negarkho@buffalo.edu

Extended author information available on the last page of the article



**Fig. 1** Annual wildfire burned area in million acres (blue) and annual federal firefighting cost in billion dollars (red) across the US, corrected for the CPI-U inflation rate (US Bureau of Labor Statistics 2021). The blue and red lines show the 5-year moving average of the burned area and firefighting cost, respectively (National Interagency Fire Center 2021)

natural, social, economic, and health systems. Extreme wildfires are now a persistent threat in regions across the country and beyond what was once considered the fire season, examples of which are the 2016 Gatlinburg Fire in the Southeast (Park 2016) and the 2021 Marshall Fire in late December (Seaman et al. 2021). At present, about 32% of Americans live in areas designated as the wildland-urban interface (WUI), the geographical region where structures and other human development meet or intermingle with wildland or vegetative fuels (IWUIC 2021; Mockrin et al. 2022). Nationwide expansion of WUI has been significant from 1990 to 2010 in terms of both the number of new houses (from 30.8 to 43.4 million—41% growth) and the land area (from 581,000 to 770,000 km<sup>2</sup>—33% growth) (Radeloff et al. 2018). A study by Iglesias et al. (Iglesias et al. 2021) indicated an 18-fold increase in density and a tenfold growth of the exposed built-up area to wildfire hazards between 1945 and 2015.

The expansion of WUI has historically triggered aggressive fire suppression, which resulted in excessive fuel accumulation on the ground (Calkin et al. 2015). Fuel accumulation along with climatic changes leading to long, hot, and dry fire seasons have resulted in a rise in the frequency, extent, and intensity of wildland fires (Abatzoglou and Williams 2016; Brown et al. 2004). Also, WUI expansion has been accompanied by increased human activity and infrastructure that are now responsible for starting 84% of all wildfires, resulting in a greatly expanded fire season length, total burned area, and impact (Balch et al. 2017). Figure 1 displays the overall increasing trend in the total burned area from 1980 to

2020, which is correlated with federal firefighting costs. The firefighting cost represents only a small fraction of the total cost of wildfires (see, e.g., (Association for Fire Ecology et al. 2015; Headwaters Economics 2018)), an accurate assessment of which is generally deemed to be out of reach at present. Although burned area, shown in Fig. 1, might not be the best metric to measure the impacts of wildfire (Kolden 2020), there could be a correlation between burned area and some of the negative impacts of wildfire, such as smoke on nearby and downwind communities or the incident duration that correlates to lengthened disruptions in recreation-dependent economies.

The consequences of wildland-urban fire disasters in WUI communities become even more exacerbated considering the often limited social, financial, and institutional capacities of WUI communities to prepare for, respond to, cope with, and recover from disasters. Also, socially vulnerable populations in WUI communities typically experience greater impacts from disasters (e.g., Davies et al. 2018; Gwynne et al. 2019; McDaniel et al. 2021; Thomas et al. 2009)).

### 1.1 Risk assessment framework

Managing future wildfires and their multi-dimensional impacts requires moving from traditional reactive response and suppression to deploying proactive policies, strategies, and interventional programs to reduce various dimensions of risk (USDA and DOI 2007; USHF 2006; WH EO 2016). Risk reduction strategies may include mitigation programs (e.g., fuel treatment, home hardening, land use planning), preparedness programs (e.g., public education, defensible space, public safety power shutoffs), and improved response strategies (e.g., fire detection and tracking, early warning, new suppression technologies) (Iglesias et al. 2022). Nevertheless, decision-making for risk reduction necessitates the quantification of risk based on a holistic assessment of wildfire impacts to determine the following: what policies and programs could be more effective, at what level and extent the programs should be implemented, where the investment should go, what new technical and technological solutions can be more effective, and how the adequacy of hazard mitigation programs can be evaluated.

The limitations in existing funding and resources necessitate optimal resource allocation and decision-making based on a comparison of different intervention scenarios and investment strategies. The decision-making process can be shepherd through a holistic analytical framework to measure the risk of wildfires, especially in the WUI communities. The risk assessment framework should model the effects of various intervention actions and compare investment costs versus risk reduction benefits. The estimated risk can be compared with the acceptable or tolerable thresholds to determine the adequacy of the implemented wildfire mitigation, preparedness, and response programs.

The concept of wildland fire risk assessment is not new (Finney 2005). Various fire risk assessment approaches and products have been established and used in different capacities with often different interpretations of the risk and diverse or simplified procedures for its assessment (e.g., CA Office of the State Fire Marshal 2021; CA Public Utility Commission 2021; FEMA 2021; Jeffery et al. 2019; Scott et al. 2013)). For example, the existing net value change (NVC) framework (Scott et al. 2013) has at times failed to integrate multiple stakeholder concerns and typically blends multiple resources and assets (e.g., habitat, timber) during the evaluation process into a common, importance-weighted metric that can mask performance variations for individual assessments (Essen et al. 2021; McEvoy et al. 2021). Given the need, Iglesias et al. (2022) propose a risk framework to include

interactions between humans and the natural environment, and to identify fires with potentially devastating impacts on communities. The diversity in existing approaches, and lack of a unified analytical framework that properly captures uncertainties and the impact of decisions across social, ecological, and technical systems is a critical shortcoming that may prevent effective decision-making related to risk reduction investments, considering prevention, mitigation, response, and recovery phases.

This paper presents the perspectives on a probabilistic risk assessment framework (ISO 2018) for wildfires. Lessons learned from other disciplines are used as a roadmap and extended for wildfire risk assessment. Stemming from the earthquake engineering field and later adopted for other hazards such as hurricanes, floods, and building fires (Hamilton 2011; Lange et al. 2014), performance-based engineering involves probabilistic risk assessment methodology that supports decision-making by defining a series of performance goals (e.g., life safety versus remaining operational after an event) considering various impacts and losses (e.g., loss of life versus business interruptions) (Deierlein et al. 2003; PEER 2021). Performance-based engineering provides a methodology to incorporate inputs from different stakeholders (FEMA 2006). The successful adoption of the approach to a series of hazards is evidence of its flexibility; thus, the performance-based methodology is extended to the wildfire hazard in this paper.

Our framework characterizes the dynamic risk as a spatial probability density function (SPDF) of loss. Loss can include different “decision variables” depending on the stakeholder’s needs and identity, and consequently, risk can be characterized as a joint SPDF or a set of marginal SPDFs. It is noted that the potential benefits of wildland fires as an essential component of the ecosystem are acknowledged; however, the framework here intends to systematically measure the negative consequences of the wildfire hazard. Further details will be delineated in the following sections. Before proceeding, it should be noted that some of the outlined concepts and modeling components may not be currently available and would require future research and development, as will be discussed. This, however, will not prevent us from depicting the perspectives on a wildfire risk assessment framework and highlighting the research needs required to fully operationalize it.

## 2 Application of a probabilistic risk assessment framework to wildfire hazard

We build upon the mature risk assessment framework developed by the Pacific Earthquake Engineering Research (PEER) center (PEER 2021) and propose a framework for wildfire probabilistic risk assessment. Presented in Fig. 2, the proposed approach provides an

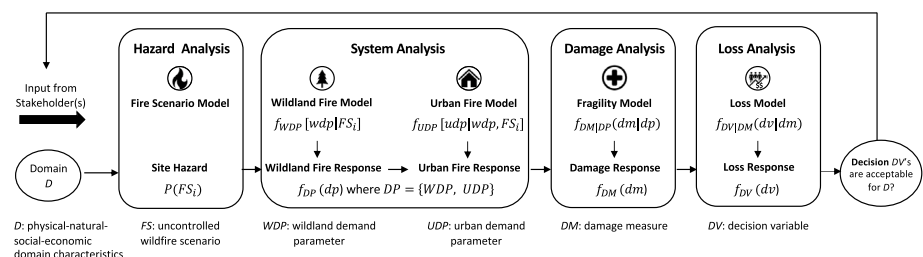


Fig. 2 The framework for wildfire probabilistic risk assessment

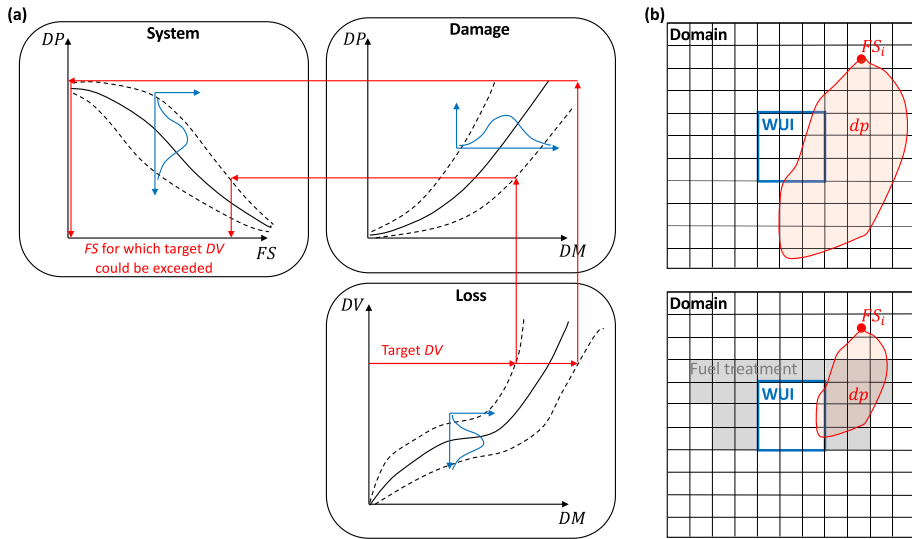
integrated holistic computational framework to propagate and integrate uncertainties from hazard (i.e., fire scenario), system (e.g., wildland fire and urban fire), and damage analyses to quantify risk as the SPDF of loss. Each of the four boxes in Fig. 2 is a model or set of models that depend on uncertain inputs and parameters and solve stochastic or scenario-based simulations. The output of each box is mathematically expressed in a probabilistic form and propagates the uncertainties into the next box as inputs. The analysis steps are linked together from left to right in Fig. 2 through the total probability integral, which can be calculated numerically to arrive at the SPDF of loss. Loss is characterized by using a set of decision variables selected in coordination with stakeholders to ensure proper communication and effective decision-making. In selecting the decision variables, physical, social, economic, environmental, and health impacts may be considered (where impact reflects consequences of wildfire, including damage and/or loss). The selected spatial and temporal scales to evaluate risk are driven by the stakeholder needs and identity. It is also shown that the effectiveness of strategies to reduce fire risk depends on the scale at which the risk is being evaluated (Kristin et al. 2021). Here, the spatial resolution for the risk assessment procedure is selected to capture the wildfire evolution in a WUI community (i.e., order of meters), but the methodology can be applied to larger spatial resolutions considering the objectives. The framework provides a systematic and modular approach for different disciplines to contribute to a unified and convergent methodology for wildfire risk assessment.

Equation 1 expresses the mathematical formulation of the framework presented in Fig. 2. In this equation,  $FS$  is an uncontrolled wildfire scenario,  $WDP$  is the wildland demand parameter (e.g., fire spread rate, fire energy release, flame height,  $CO_2$  emission),  $UDP$  is the urban demand parameter (e.g., fire spread rate in a community),  $DP$  is the combined wildland and urban demand parameters,  $DM$  is the damage measure (e.g., number of burned structures, air quality index, consequences on human health, and physical, economic, social, and ecosystem impacts),  $DV$  is the decision variable (e.g., direct or indirect monetary loss and/or other metrics of loss). The description of each variable is provided in detail in the sections to follow. The variables  $WDP$ ,  $UDP$ ,  $DP$ ,  $DM$ , and  $DV$  are modeled as random variables (or random vectors), the uncertainties of which are characterized by SPDFs denoted as  $f(\cdot)$ . The analysis results in Eq. 1 are integrated through conditional probabilities and summed over  $n$  probable uncontrolled wildfire scenarios to arrive at the SPDF of loss for a given WUI site. The process in Eq. 1 should be repeated for different sites within the domain exhaustively to obtain the spatial SPDF of risk. The formulation assumes that the variables in the analysis are conditionally independent. Relevant parameters in each part of the analysis are taken as random variables (e.g., weather condition, fuel parameters, ignitability of structures, among others), the uncertainties of which are propagated into the resulting  $DP$ ,  $DM$ , and  $DV$  variables. Certain parameters, such as topography, the layout of the buildings, etc., can be taken as deterministic.

$$f_{DV}(dv) = \sum_{i=1}^n \iint f_{DV|DM}(dv|dm) \cdot f_{DM|DP}(dm|dp) \cdot f_{DP|FS}(dp|FS_i) \cdot P(FS_i) d_{dm} d_{dp} \quad (1)$$

where  $DP = \{WDP, UDP\}$

Figure 3 shows the schematics of the proposed framework, where  $FS_i$  in the domain of analysis is one probable uncontrolled wildfire scenario. The system, damage, and loss analyses are performed for all probable cases and by considering uncertainties. Given a target threshold for  $DV$ , the range of  $FS$  for which the target  $DV$  could be exceeded can be backtracked through  $DM$  and  $DV$  variables. Figure 3b illustrates the effect of a sample mitigation action (here, fuel treatment) on the demand parameter  $DP$  (e.g., fire energy release,



**Fig. 3** Schematics of **a** the framework for wildfire probabilistic risk assessment where uncertainties associated with the system, damage, and loss analyses are included, **b** comparison of the effect of fuel treatment on the demand parameter  $DP$  (e.g., fire energy release, fire spread rate). A lower  $DP$  leads to lower levels of damage and loss

fire spread rate). Lowering the  $DP$  maps to lower damage and losses. The following subsections discuss each analysis stage in detail.

## 2.1 Hazard analysis

The hazard analysis quantifies the likelihood of an uncontrolled wildfire scenario ( $FS$ ). This includes fire ignition and the associated weather and environmental conditions. The analysis is location- and time-dependent; that is, the likelihood of ignition and the associated weather and environmental conditions vary with location in the defined domain and over time (short- vs. long-term). All potential ignitions and the associated weather and environmental conditions should be considered in the hazard analysis, depending on the assumed models.

The source of wildfire ignition could be natural (e.g., lightning strikes), anthropogenic (e.g., escaped campfires), or malfunctions in infrastructure systems (e.g., failure in power transmission system). Different methodologies have been applied to model wildfire ignitions and study the influence of various predictors on the likelihood of wildfire ignition (Martín et al. 2019; Prestemon et al. 2013). In general, statistical and machine learning models show a correlation between the probability of ignition and anthropogenic factors (such as distance to the nearest road or the nearest house) (Bar Massada et al. 2012; D'Este et al. 2020; Mann et al. 2016). Land cover, state of the fuel, and drought are additional factors that influence the likelihood of wildfire ignition (Bar Massada et al. 2012; D'Este et al. 2020; Preisler et al. 2011; Riley et al. 2013).

A comprehensive risk assessment at a range of temporal and spatial scales and fidelity levels requires appropriate weather and climate information. Historical distribution of

hot, dry, and windy (HDW) conditions, with a selection of top percentile events (e.g., > 90 percentile), can be collected to represent the fire weather conditions for the considered area (Burgan et al. 1998; Srock et al. 2018; Stocks et al. 1989; USGS 2018). Variables can be treated either separately (e.g., just wind) or jointly (e.g., joint-probability density function, SPDF, of wind and relative humidity). The weather conditions can be treated as climatologically stationary to conduct the risk assessment using 30-year baselines. Alternatively, a long-term risk assessment accounting for the effects of climate change requires climate predictions combined with landscape change predictions (e.g., (Liu et al. 2015)). At sub-seasonal to seasonal (S2S) scales, operational forecasting systems (e.g., Climate Forecast System—CFSv2, European Centre for Medium-Range Weather Forecasts System5) can provide risk assessment for an upcoming fire season. For shorter time scales, high-resolution ensemble weather prediction models (e.g., Short Range Ensemble Forecast (SREF), Global Ensemble Forecast System (GEFS)) can be assembled to produce day-to-weeks ahead forecasts wherein the wildfire spread in the system analysis for a given location in the wildland can be driven by forecast weather rather than the historical distribution. For actionable risk assessment, different temporal scales must be combined with appropriate spatial scales. This is particularly pertinent considering that fires are becoming larger and more frequent and in closer proximity to communities (Iglesias et al. 2022). In addition to weather variables, to better estimate the wildland fire risk, fuel characteristics and conditions can be included using Fire Potential Index (Preisler et al. 2009) and Energy Release Component fire danger rating index (e.g., Finney et al. 2011a) as a proxy for live and dead fuel moisture.

The output of the hazard analysis—i.e., wildfire ignitions and the associated weather and environmental conditions that lead to uncontrolled wildfires, with their probabilities of occurrence—is the input to the system analysis in the wildland, as discussed in the next section.

## 2.2 System analysis: wildland fire model

System analysis in the wildland characterizes the rate and direction of fire spread, which can be extended to quantify other measures, such as plume rise and smoke transport or CO<sub>2</sub> emissions, based on the needs in the subsequent damage and loss analysis steps. Data from historical fires can be used to obtain the statistical distribution of fire growth rates (e.g., acres per day) and the primary direction of spread (e.g., the major axis of an approximate ellipse). For example, the considered domain can be discretized into a grid, and fires within a specified radius of a grid point—i.e., the region of influence, can be aggregated to produce SPDFs of growth rate and direction of spread (Calkin et al. 2011; Noonan-Wright et al. 2011). The spatial resolution of the analysis (e.g., grid size) and the selected radius to define the region of influence should be considered to capture the effects of relevant wild-fire scenarios.

Performing a systematic analysis of past wildfires to obtain the distributions of rate and direction of fire spread is an option but is subjected to two drawbacks: (1) there may not be adequate historical data on extreme wildfire events, and (2) changes in climate, fuel characteristics, human settlements, and weather patterns may lead to unique wildfire spread and behavior that is not captured in historical data. To address the first issue, it is possible to conduct fire simulations for every grid point in the domain using a climatological selection of the upper percentile HDW days (obtained from the hazard analysis). To address the second issue mentioned above, forecast weather data (obtained from hazard analysis) can be



used when setting up the simulations to capture the potential increase in risk due to climate change (Loehman et al. 2020; Riley and Loehman 2016; Riley et al. 2019). Also, a fuel (or land) model may be necessary to predict the change in the fuel characteristics due to climate effects and anthropogenic activities (Hurteau et al. 2019; Littell et al. 2018).

In general, wildfire simulations in the wildland require input on weather, land, and fuel characteristics, as well as topography. Wildfire simulations can be completed with either coupled fire-atmosphere models (e.g., WRF-Fire (Coen et al. 2013)) or uncoupled fire spread models (e.g., FSim Finney et al. 2011b). Regardless of the model type, the uncertainties in the input parameters, including those propagated from the *FS* (output of hazard analysis), should be incorporated. FSPro is an example of an existing probabilistic fire simulation process, which propagates the weather uncertainties into surface fire spread and finds the probability of a fire scenario reaching a certain location on the landscape (Finney et al. 2011b). The current wildland fire models include inherent uncertainties and modeling errors that must be quantified and propagated through the workflow (Jimenez et al. 2008; Liu et al. 2015). These are research subjects that deserve detailed investigations. For example, inaccurate characterization of the effects of ember transport and "spotting" on fire spread are important shortcomings in current simulation tools, requiring additional research.

The results of wildfire simulations can be aggregated to arrive at the distribution of the wildland demand parameter (*WDP*). Note that the simulations may be completed without considering the effects of suppression to yield the upper limits of wildfire risk in case of a scenario with no intervention. Capturing the dynamic nature of active firefighting actions is challenging (Duff and Tolhurst 2015; Plucinski 2019), and existing tools tend to use streamlined approaches to incorporate containment actions (Riley et al. 2018). The output of system analysis in the wildland, *WDP*, is an input to the urban fire model, where the defined domain contains a WUI.

### 2.3 System analysis: urban fire model

Many wildfire risk assessment procedures (Ager et al. 2019; Calkin et al. 2019; Duff and Penman 2021; Finney et al. 2011b) use outputs of simulation modeling to quantify the wildfire exposure to WUI communities but generalize the susceptibility of structures to fire as a function of flame length and based on expert judgment (Helmbrecht et al. 2016; Scott et al. 2020). The existing tools cannot be used to simulate the effect of different mitigation or preparedness actions, such as creation of defensible space and mitigations within the home ignition zone (Calkin et al. 2014), on reducing wildfire losses for a specific community. Thus, validated modeling techniques are needed to simulate fire spread within urban communities considering the characteristics of the built environment. This modeling capacity is not fully available at the moment.

Analysis of fire spread inside the built environment requires input on vegetation, structures, non-combustible areas such as roadways, and weather data to characterize the fire behavior. In a community, combustible structures contribute to fuel during an urban fire event. Structures burn slower than vegetation but contain more energy and may generate considerable embers for transport. The National Institute of Standards and Technology has formulated a procedure for data collection in WUI communities after a fire (Mell et al. 2011), but there is currently no protocol or standard for collecting, assembling, and integrating data at appropriate temporal and spatial resolutions to study or simulate fire spread in communities (Caton et al. 2017; Hakes et al. 2017). The required spatial and temporal



resolutions to track fire spread inside a community are finer than those in the wildland; that is, a fire line passes through a community in a few hours, whereas a wildfire can spread in the wildland for days or weeks. Also, capturing the fire spread between houses implies a spatial resolution on the order of meters.

There is no well-established tool or model that can simulate fire spread in urban communities considering all modes of fire spread (radiation, direct flame contact, and fire spotting) and the construction details of individual structures (e.g., number of stories, roof types). The research community has identified the need for such tools and has been developing validated models to capture the behavior of urban fuel during wildfire events (Mahmoud and Chulahwat 2018; Masoudvaziri et al. 2021). Considering this modeling capability exists, the evolution of fire spread inside the community is simulated given the physical characteristics of the community and the *WDP* (output of the wildland fire model). Uncertainties from the wildland fire model are propagated to the urban fire model through the SPDF of the *WDP*. The output of the urban fire model, characterized by the urban demand parameter (*UDP*), should be reported as a quantity that can be related to the damage analysis, such as the number of burned homes or displaced population. The urban fire model should incorporate uncertainties, such as fire spotting, building ignition criteria, etc. when simulating fire spread in a community. The stochastic simulations result in the SPDF of the *UDP*, which is an input to the damage analysis. Finally, an urban fire model is needed not only for damage and loss assessment but also for planning evacuation routes (Li et al. 2019) and allocation of firefighting resources.

## 2.4 Damage analysis

Damage analysis calculates fragility functions for pre-determined damage states as a function of the wildland and/or urban fire demand parameters (i.e., system analysis results). A fragility function provides the probability of exceeding a damage state, given the *WDP* and *UDP*, where the damage states are determined based on the range of damage measures (*DMs*) that could arise from the hazard. The input *WDP* and *UDP* are probabilistic measures from system analysis, in the form of SPDFs and propagate uncertainties from the hazard and system analyses to damage analysis. Fragility functions can be derived using different approaches, namely, empirical, analytical, expert-based judgment, and hybrid (FEMA 2018). In the empirical approach, fragility functions are extracted from the results of past observations and recorded data following wildfire events. This approach reflects the actual performance of the defined system but could also suffer from large uncertainties in the observations related to the defined *DM*. In contrast, the analytical approaches arrive at fragility functions by modeling techniques and considering the uncertainties in random variables. Expert-based fragility functions can be constructed using input from specialists. Hybrid approaches, which combine models with expert judgment, are also among the available options to derive fragility functions.

The *DM* should be representative of the performance requirements, which are stakeholder-driven. The *DMs* are input to the loss estimation process and, therefore, should be characterized, modeled, and measured based on the loss definition. They can expand across different domains, including but not limited to physical assets (e.g., number of burned homes and damaged infrastructure), health (e.g., smoke emission and air quality), economy (e.g., impact on local business), ecosystem, and climate (e.g., CO<sub>2</sub> emission) (Feo et al. 2020). Findings from other related fields, such as health effects from air pollution, can be incorporated into the proposed risk assessment framework. For example, previous research

shows that people from certain groups (e.g., children and older adults) and with lower socioeconomic status may be more vulnerable to the health impacts of air pollution (US Environmental Protection Agency 2021) and building fires (Jennings 2013). Nevertheless, further research is needed to establish a consistent method to model wildfire damage along such multiple dimensions (Iglesias et al. 2022). The output of the damage analysis serves as the input to the loss model.

## 2.5 Loss analysis

Loss analysis is the final and the most important step in the framework, which converts the results of damage analysis into decision variables (*DVs*). Each *DM*, defined in the damage analysis, can be mapped to a quantitative *DV*. The *DVs* can be defined as nonmonetary or monetary measures, which can include direct, indirect, short-, and long-term losses, and can span across different domains—i.e., physical, social, economic, health, and environmental domains—depending on stakeholder input and the defined *DM* (Feo et al. 2020; Porter et al. 2021). Examples of nonmonetary measures include, among others, loss in quality of life, burned area, number of injuries and fatalities, number of affected households, and number of people experiencing health issues due to short- or long-term effects (NASEM 2020). Examples of monetary measures include, among others, infrastructure loss, restoration cost, business interruptions, health care cost, economic loss, and rehabilitation cost.

It should be noted that monetary evaluations of especially long-term social, economic, health, and environmental losses are complex tasks (May 2007; Venn and Calkin 2011). The complexity becomes intensified when the inherent interdependencies of these impacts on human life and the often-high vulnerability of WUI populations are considered. Therefore, further research is needed to develop the knowledge and methods to understand, model, and measure the wildfire losses in a comprehensive, consistent, accurate, and fair way.

Furthermore, the characterization of loss metrics necessitates a deliberative-analytical process to include the perspectives of the spectrum of stakeholders (Webler et al. 2016; Wunder et al. 2021). The damage and consequent loss analysis processes necessitate inherent simplifications and assumptions, which should be guided through a deliberative process to determine the required analytical details. The resulting models would include inherent sources of modeling uncertainties, either recognizable and quantifiable, recognizable and indeterminate, and/or unrecognizable (i.e., due to simplification and ignorance of the complexity of the wildfire response domain). The uncertainty quantification process should be conducted with care and informed by the deliberation to ensure a *consistent crudeness* in the developed models and analytical processes. While there is a relatively mature understanding of the damage and loss analysis for earthquake hazards (Alesch et al. 2012; May 2007), the application of this process to wildfire hazards requires further research efforts.

## 3 Summary notes

The current approach toward wildfire management should change by shifting the focus from response and suppression to designing, adjusting, and, in short, engineering the risk in coordination with the spectrum of stakeholders. The cost of wildfires is much higher than the direct and immediate losses considering all its various dimensions. Given the

limited resources, the wildfire risk for a given location should be quantified, and the effects of mitigation actions should be evaluated to understand the cost-versus-benefit from a unified perspective. The critical tasks of prioritizing resources and allocating funds for implementing mitigation actions and policies can be guided by identifying the vulnerable locations and lowering the risk to acceptable levels with stakeholder feedback.

Although the outlined probabilistic risk assessment framework may provide a robust analytical approach for wildfire risk engineering as it has in earthquake engineering (FEMA 2018), we currently face a critical lack of knowledge toward its development and implementation in several important areas. Overcoming the lack of knowledge necessitates systematic, convergent, and coordinated research efforts. The successful execution of research requires attention to some key hurdles summarized below to promote broader thinking:

- The presented framework in Fig. 2 begins with a hazard and system analysis, but there is a lack of consistent interpretation and understanding of the various damage and loss aspects of wildfires (Feo et al. 2020). This is due to the complexity of the problem domain and the many dimensions along which wildfire hazards can impact lives, and the built and natural environments. In addition, siloed efforts with different agencies and working groups focusing on different aspects of the problem hinder the development and implementation of integrated solutions (Stavros et al. 2021). As mentioned above, converging on a comprehensive characterization of wildfire damage, loss, and the resulting risk requires an analytical-deliberative process. Deliberation is a process through which researchers, analysts, and stakeholders (including all interested and affected parties) should discuss, ponder, exchange observations and views, reflect upon information and judgments, and attempt to converge on a mutually agreeable conclusion (Miller et al. 2021). The deliberation process should iteratively guide and be guided by data and models through the analytical processes (National Research Council 1996; Petak 2002).
- The outcome of the analytical-deliberative process may guide the variety of analytical tools and models that need to be developed for different stages of risk assessment. Nevertheless, all models include inherent uncertainties. In the present context, an important source of uncertainty is the complexity and interdependencies among different damage and loss components, which need to be established to capture the overall wildfire impacts. Characterizing the complex system may necessitate different levels of simplifications and assumptions. This can result in an inconsistent crudeness in various models and modeling approaches, which can be alleviated by correctly understanding and quantifying the underlying uncertainties in the models and data.
- If executed correctly, the resulting risk metrics and cost–benefit analyses can be used to guide actionable risk-reduction decisions and policies. However, policy design is never solely based on scientific assessment, which inevitably bears uncertainties and involves ingestion by and decision-making through a political system (Petak 2002). As such, effective policy design can be facilitated through an early-stage inclusion and involvement of the social, political, legal, and regulatory stakeholders in the deliberations to define the various risk limits, including acceptable/tolerable risk and transferrable risk (e.g., through insurance) (Meacham and van Straalen 2018; Meacham et al. 2021). Quantifying the acceptable/tolerable risk requires a trade-off between vulnerability (Cutter et al. 2003), and economic and political drivers with a goal of achieving equity in outcomes.

- Finally, and perceptibly, risk-reduction interventions can benefit from new technical and technological developments (e.g., new fuel management techniques, new fire-resilient construction techniques, new suppression techniques, and new digital technologies for ignition detection, fire-spread monitoring, fire simulation, and response coordination) (Wildfire Technology Funders Group 2022). The probabilistic risk assessment framework and its capability for cost–benefit analysis can also be used to investigate the potential value of new technologies, which can guide the future investment in research and technology development.

**Funding** This work was supported through the National Science Foundation's Leading Engineering for America's Prosperity, Health, and Infrastructure (LEAP HI) program by grant number CMMI-1953333 and the division of Engineering Education and Centers (EEC) program by planning grant number 2124455. Opinions and perspectives expressed in this study are those of the authors and do not necessarily reflect the sponsor's views. Also, this research was supported by the US Department of Agriculture, Forest Service. The findings and conclusions in this report are those of the author(s) and should not be construed to represent any official USDA or US Government determination or policy. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the US government.

## Declarations

**Conflict of interest** The authors have no relevant financial or non-financial interests to disclose.

## References

- Abatzoglou JT, Williams AP (2016) Impact of anthropogenic climate change on wildfire across western US forests. *Proc Natl Acad Sci USA (PNAS)* 113(42):11770–11775. <https://doi.org/10.1073/pnas.1607171113>
- Ager AA, Day MA, Palaiologou P, Houtman RM, Ringo C, Evers CR (2019) *Cross-boundary wildfire and community exposure: a framework and application in the Western US* Gen. Tech. Rep. RMRS-GTR-392. Forest Service US Department of Agriculture, Rocky Mountain Research Station,, Fort Collins, CO
- Alesch D, Arendt L, Petak W (2012) Natural hazard mitigation policy: implementation, organizational choice, and contextual dynamics. Springer, Dordrecht. <https://doi.org/10.1007/978-94-007-2235-4>
- Association for Fire Ecology, International Association of Wildland Fire, The Nature Conservancy (2015) *Reduce wildfire risks or we will continue to pay more for fire disasters*. Position Statement. Retrieved August 2021 from <https://www.iawfonline.org/article/reduce-wildfire-risks-or-pay-more-for-fire-disasters/>
- Balch JK, Bradley BA, Abatzoglou JT, Nagy RC, Fusco EJ, Mahood AL (2017) Human-started wildfires expand the fire niche across the United States. *Proc Natl Acad Sci USA (PNAS)* 114(11):2946–2951. <https://doi.org/10.1073/pnas.1617394114>
- Bar Massada A, Radeloff V, Stewart S, Syphard A (2012) Wildfire ignition-distribution modelling: a comparative study in the Huron-Manistee National Forest, Michigan, USA. *Int J Wildland Fire* 22:174–183. <https://doi.org/10.1071/WF11178>
- Brown TJ, Hall BL, Westerling AL (2004) The impact of twenty-first century climate change on wildland fire danger in the Western United States: an applications perspective. *Clim Change* 62:365–388
- Burgan RE, Klaver RW, Klarer JM (1998) Fuel models and fire potential from satellite and surface observations. *Int J Wildland Fire* 8(3):159–170. <https://doi.org/10.1071/WF9980159>
- CA Office of the State Fire Marshal (2021) *Fire Hazard Severity Zones Maps*. Retrieved August 2021 from <https://osfm.fire.ca.gov/divisions/wildfire-planning-engineering/wildland-hazards-building-codes/fire-hazard-severity-zones-maps/>

- CA Public Utility Commission (2021) *CPUC High Fire Threat District (HFTD)*. Retrieved August 2021 from: <https://www.arcgis.com/apps/webappviewer/index.html?id=5bdb921d747a46929d9f00dbdb6d0fa2>
- Calkin D, Price O, Salis M (2019) WUI risk assessment at the landscape level. In: Manzello S (ed) *Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires*. Springer, Cham, pp 1184–1195. <https://doi.org/10.1007/978-3-319-52090-2>
- Calkin D, Thompson M, Finney M, Hyde K (2011) A real-time risk assessment tool supporting wildland fire decisionmaking. USDA Forest Service/UNL Faculty Publications
- Calkin DE, Cohen JD, Finney MA, Thompson MP (2014) How risk management can prevent future wildfire disasters in the wildland-urban interface. *Proc Natl Acad Sci USA (PNAS)* 111(2):746–751. <https://doi.org/10.1073/pnas.1315088111>
- Calkin DE, Thompson MP, Finney MA (2015) Negative consequences of positive feedbacks in US wild-fire management. *Forest Ecosyst*. <https://doi.org/10.1186/s40663-015-0033-8>
- Caton SE, Hakes RSP, Gorham DJ, Zhou A, Gollner MJ (2017) Review of pathways for building fire spread in the wildland urban interface Part I: exposure conditions. *Fire Technol* 53(2):429–473. <https://doi.org/10.1007/s10694-016-0589-z>
- Coen JL, Cameron M, Michalakos J, Patton EG, Riggan PJ, Yedinak KM (2013) WRF-Fire: Coupled weather–wildland fire modeling with the weather research and forecasting model. *J Appl Meteorol Climatol* 52:16–38
- Cutter SL, Boruff B, Shirley WL (2003) Social vulnerability to environmental hazards. *Soc Sci Quart* 84(2):242–261. <https://doi.org/10.1111/1540-6237.8402002>
- D'Este M, Ganga A, Elia M, Lovreglio R, Giannico V, Giuseppe Colangelo G, Laforteza R, Sanesi G (2020) Modeling fire ignition probability and frequency using Hurdle models: a cross-regional study in Southern Europe. *Ecol Process*. <https://doi.org/10.1186/s13717-020-00263-4>
- Davies IP, Haugo RD, Robertson JC, Levin PS (2018) The unequal vulnerability of communities of color to wildfire. *PLoS ONE* 13(11):e0205825
- Deierlein GG, Krawinkler H, Cornell CA (2003) A framework for performance-based earthquake engineering. Proceedings of the 2003 Pacific conference on earthquake engineering, New Zealand Society for Earthquake Engineering, Christchurch, New Zealand.
- Duff TJ, Penman TD (2021) Determining the likelihood of asset destruction during wildfires: modelling house destruction with fire simulator outputs and local-scale landscape properties. *Saf Sci* 139:105196
- Duff TJ, Tolhurst KG (2015) Operational wildfire suppression modelling: a review evaluating development, state of the art and future directions. *Int J Wildland Fire* 24(6):735–748
- Essen M, McCaffrey S, Abrams J, Paveglio T (2021) Improving wildfire management outcomes: shifting the paradigm of wildfire from simple to complex risk. *J Environ Plann Manag*. <https://doi.org/10.1080/09640568.2021.2007861>
- FEMA (2006) FEMA-445: Next-generation performance-based seismic design guidelines, profram plan for new and existing buildings. Washington, DC
- FEMA (2018) Next-generation methodology for seismic performance assessment of buildings. Prepared by the Applied Technology Council for the Federal Emergency Management Agency, Washington, DC. <https://femap58.atcouncil.org/>
- FEMA (2021) National Risk Index. Retrieved August 2021 from <https://hazards.fema.gov/nri/map>
- Feo TJ, Mace AJ, Brady SE, Lindsey B (2020) The costs of wildfire in California, An independent review of scientific and technical information. A commissioned report prepared by the California Council on Science and Technology, Sacramento, CA
- Finney MA (2005) The challenge of quantitative risk analysis for wildland fire. *Forest Ecol Manag* 211(1–2):97–108
- Finney MA, Grenfell IC, McHugh CW, Seli RC, Trethewey D, Stratton RD, Brittain S (2011a) A method for ensemble wildland fire simulation. *Environ Model Assess* 16:153–167. <https://doi.org/10.1007/s10666-010-9241-3>
- Finney MA, McHugh CW, Grenfell IC, Riley KL, Short KC (2011b) A simulation of probabilistic wildfire risk components for the continental United States. *Stoch Environ Res Risk Assess* 25(7):973–1000. <https://doi.org/10.1007/s00477-011-0462-z>
- Gwynne S, Ronchi E, Bénichou N, Kinatader M, Kuligowski E, Gomaa I, Adelzadeh M (2019) Modeling and mapping dynamic vulnerability to better assess WUI evacuation performance. *Fire Mater* 43:644–660. <https://doi.org/10.1002/fam.2708>
- Hakes RSP, Caton SE, Gorham DJ, Gollner MJ (2017) A review of pathways for building fire spread in the wildland urban interface Part II: response of components and systems and mitigation strategies in the United States. *Fire Technol* 53(2):475–515. <https://doi.org/10.1007/s10694-016-0601-7>

- Hamilton SR (2011) Performance-based fire engineering for steel framed structures: a probabilistic methodology Stanford University. Sanford, CA, USA. <https://stacks.stanford.edu/file/druid:mh477sw7685/Dissertation%20Final%20Version-augmented.pdf>
- Headwaters Economics (2018) The Full Community Costs of Wildfire. Retrieved August 2021 from <https://headwaterseconomics.org/wp-content/uploads/full-wildfire-costs-report.pdf>
- Helmbrecht D, Gilbertson-Day J, Scott JH, Hollingsworth L (2016) Wildfire risk to residential structures in the Island Park Sustainable Fire Community: Caribou-Targhee National Forest. US Department of Agriculture, Missoula, MT
- Hurteau MD, Liang S, Westerling AL, Wiedinmyer C (2019) Vegetation-fire feedback reduces projected area burned under climate change. *Sci Rep*. <https://doi.org/10.1038/s41598-019-39284-1>
- Iglesias V, Braswell AE, Rossi MW, Joseph MB, McShane C, Cattau M, Koontz MJ, McGlinchy J, Nagy RC, Balch J, Leyk S, Travis WR (2021) Risky development: increasing exposure to natural hazards in the United States. *Earth's Future* 9(7):e2020EF001795. <https://doi.org/10.1029/2020EF001795>
- Iglesias V, Stavros N, Balch JK, Barrett K, Cobian-Iñiguez J, Hester C, Kolden CA, Leyk S, Nagy RC, Reid CE, Wiedinmyer C, Woolner E, Travis WR (2022) Fires that matter: reconceptualizing fire risk to include interactions between humans and the natural environment. *Environ Res Lett* 17(4):045014. <https://doi.org/10.1088/1748-9326/ac5c0c>
- Risk Management: ISO 31000, (2018). <https://www.iso.org/standard/65694.html>
- IWUIC (2021) International Wildland-Urban Interface Code. International Code Council
- Jeffery T, Yerkes S, Moore D, Calgiano F, Turakhia R (2019) 2019 Wildfire Risk Report. CoreLogic. <https://storymaps.arcgis.com/stories/cb987be2818a4013a66977b6b3900444>
- Jennings CR (2013) Social and economic characteristics as determinants of residential fire risk in urban neighborhoods: a review of the literature. *Fire Saf J* 62:13–19
- Jimenez E, Hussaini MY, Goodrick S (2008) Quantifying parametric uncertainty in the Rothermel model. *Int J Wildland Fire* 17(5):638–649
- Kolden C (2020) Wildfires: count lives and homes, not hectares burnt. *Nature* 586(7827):9–9
- Kristin HB, Rupert S, Werner R, Monica GT (2021) Can we manage a future with more fire? Effectiveness of defensible space treatment depends on housing amount and configuration. *Landscape Ecol* 36(2):309–330. <https://doi.org/10.1007/s10980-020-01162-x>
- Lange D, Devaney S, Usmani A (2014) An application of the PEER performance-based earthquake engineering framework to structures in fire. *Eng Struct* 66:100–115
- Li D, Cova TJ, Dennison PE (2019) Setting wildfire evacuation triggers by coupling fire and traffic simulation models: a spatiotemporal GIS approach. *Fire Technol* 55:617–642
- Littell JS, McKenzie D, Peterson DL, Westerling AL (2009) Climate and wildfire area burned in western US ecoprovinces, 1916–2003. *Ecol Appl* 19(4):1003–1021
- Littell JS, McKenzie D, Wan HY, Cushman SA (2018) Climate change and future wildfire in the western United States: an ecological approach to nonstationarity. *Earth's Future* 6:1097–1111
- Liu Y, Jimenez E, Hussaini MY, Ökten G, Goodrick S (2015) Parametric uncertainty quantification in the Rothermel model with randomised quasi-Monte Carlo methods. *Int J Wildland Fire* 24(3):307–316
- Loehman RA, Keane RE, Holsinger LM (2020) Simulation modeling of complex climate, wildfire, and vegetation dynamics to address wicked problems in land management. *Front for Global Change*. <https://doi.org/10.3389/ffgc.2020.00003>
- Mahmoud H, Chulawat A (2018) Unraveling the complexity of wildland urban interface fires. *Sci Rep* 8(1):1–12
- Mann ML, Battlori E, Moritz MA, Waller EK, Berck P, Flint AL, Flint LE, Dolfi E (2016) Incorporating anthropogenic influences into fire probability models: effects of human activity and climate change on fire activity in California. *PLoS ONE* 11(4):e0153589. <https://doi.org/10.1371/journal.pone.0153589>
- Martín Y, Zúñiga-Antón M, Mimbreno MR (2019) Modelling temporal variation of fire-occurrence towards the dynamic prediction of human wildfire ignition danger in northeast Spain. *Geomat Nat Hazards Risk* 10(1):385–411. <https://doi.org/10.1080/19475705.2018.1526219>
- Masoudvaziri N, Szasdi Bardales FJ, Keskin OK, Sarreshtehdari A, Sun K, Elhami Khorasani N (2021) Streamlined wildland-urban interface fire tracing (SWUIFT): modeling wildfire spread in communities. *Environ Model Softw* 143:105097
- May P (2007) Societal implications of performance-based earthquake engineering (PEER Report, Issue. B. University of California, California, US
- McDaniel J, Adams MDO, Charnley S (2021) Reducing fuels and advancing equity: Incorporating environmental justice into hazardous fuels management. Science Findings, Forest Service US Department of Agriculture, Pacific Northwest Research Station.
- McEvoy A, Kerns BK, Kim JB (2021) Hazards of risk: Identifying plausible community wildfire disasters in low-frequency fire regimes. *Forests* 12(7):934




- Meacham BJ, van Straalen I (2018) A socio-technical system framework for risk-informed performance-based building regulation. *Build Res Inf* 46(4):444–462. <https://doi.org/10.1080/09613218.2017.1299525>
- Meacham BJ, van Straalen IJ, Ashe B (2021) Roadmap for incorporating risk as a basis of performance objectives in building regulation. *Saf Sci* 141:105337. <https://doi.org/10.1016/j.ssci.2021.105337>
- Mell W, Ridenour K, McNamara, D (2011) Initial Reconnaissance of the 2011 Wildland-Urban Interfaces Fires in Amarillo, Texas (Technical Note 1708). National Institute of Standards and Technology, Gaithersburg, MD
- Miller C, Higuera PE, McWethy DB, Metcalf AL, Metcalf EC, Black AE, Clarke L, Hodge H (2021) Developing strategies to support social-ecological resilience in flammable landscapes: A structured approach for natural resource managers and other stakeholders. *Res. Note RMRS-RN-92*, Forest Service US Department of Agriculture, Rocky Mountain Research Station, Fort Collins, CO
- Mockrin MH, Helmers D, Martinuzzi S, Hawbaker TJ, Radeloff VC (2022) Growth of the wildland-urban interface within and around US National Forests and Grasslands, 1990–2010. *Landscape Urban Plann* 104283:218
- NASE. (2020) Implications of the California Wildfires for Health Communities and Preparedness. Proceedings of a Workshop. The National Academies Press, Washington, DC. <https://doi.org/10.17226/25622>
- National Interagency Fire Center. (2021). *Fire Information and Statistics*. Retrieved September 2021 from [https://www.nifc.gov/fireInfo/fireInfo\\_statistics.html](https://www.nifc.gov/fireInfo/fireInfo_statistics.html)
- National Research Council (1996) Understanding risk: Informing decisions in a democratic society. Washington, DC
- Noonan-Wright EK, Opperman TS, Finney MA, Zimmerman GT, Seli RC, Elenz LM, Calkin DE, Fiedler JR (2011) Developing the US wildland fire decision support system. *Journal of Combustion* 2011:168473. <https://doi.org/10.1155/2011/168473>
- Park M (2016) Wildfires blaze in Gatlinburg, TN; thousands evacuated. The CNN. <https://www.cnn.com/2016/11/28/us/southern-fires-gatlinburg-smokies/index.html>
- PEER (2021) Pacific Earthquake Engineering Research Center. Retrieved June 2021 from <https://peer.berkeley.edu>
- Petak W (2002) Earthquake resilience through mitigation: A system approach International Institute for Applied Systems Analysis, Laxenburg, Austria
- Plucinski MP (2019) Contain and control: wildfire suppression effectiveness at incidents and across landscapes. *Curr Forestry Rep* 5(1):20–40. <https://doi.org/10.1007/s40725-019-00085-4>
- Porter KA, Scawthorn CR, Sandink D (2021) An impact analysis for the national guide for wildland-urban interface fires. Prepared for the National Research Council of Canada, Institute for Catastrophic Loss Reduction, Toronto, ON
- Preisler HK, Burgan RE, Eidenshink JC, Klaver JM, Klaver RW (2009) Forecasting distributions of large federal-lands fires utilizing satellite and gridded weather information. *Int J Wildland Fire* 18(5):508–516
- Preisler HK, Westerling AL, Gebert KM, Munoz-Arriola F, Holmes TP (2011) Spatially explicit forecasts of large wildland fire probability and suppression costs for California. *Int J Wildland Fire* 20(4):508–517. <https://doi.org/10.1071/WF09087>
- Prestemon JP, Hawbaker TJ, Bowden M, Carpenter J, Brooks MT, Abt KL, Sutphen R, Scranton S (2013) Wildfire ignitions: a review of the science and recommendations for empirical modeling. General Technical Report SRS-171, Forest Service US Department of Agriculture, Southern Research Station
- Radeloff VC, Helmers DP, Kramer HA, Mockrin MH, Alexandre PM, Bar-Massada A, Butsic V, Hawbaker TJ, Martinuzzi S, Syphard AD, Stewart SI (2018) Rapid growth of the US wildland-urban interface raises wildfire risk. *Proc Natl Acad Sci USA (PNAS)* 115(13):3314–3319. <https://doi.org/10.1073/pnas.1718850115>
- Riley KL, Abatzoglou JT, Grenfell IC, Klene AE, Heinsch FA (2013) The relationship of large fire occurrence with drought and fire danger indices in the western USA, 1984–2008: the role of temporal scale. *Int J Wildland Fire* 22(7):894–909. <https://doi.org/10.1071/WF12149>
- Riley KL, Loehman RA (2016) Mid-21st-century climate changes increase predicted fire occurrence and fire season length, Northern Rocky Mountains, United States. *Ecosphere* 7(11):e01543. <https://doi.org/10.1002/ecs2.1543>
- Riley KL, Thompson MP, Scott JH, Gilbertson-Day JW (2018) A model-based framework to evaluate alternative wildfire suppression strategies. *Resources* 7(1):4. <https://doi.org/10.3390/resources7010004>
- Riley KL, Williams AP, Urbanski SP, Calkin DE, Short KC, O'Connor CD (2019) Will landscape fire increase in the future? A systems approach to climate, fire, fuel, and human drivers. *Curr Pollut Rep* 5(2):9–24. <https://doi.org/10.1007/s40726-019-0103-6>



- Scott JH, Gilbertson-Day JW, Moran C, Dillon GK, Short KC, Vogler KC (2020) Wildfire risk to communities: spatial datasets of landscape-wide wildfire risk components for the United States. Forest Service Research Data, Fort Collins. <https://doi.org/10.2737/RDS-2020-0016>
- Scott JH, Thompson MP, Calkin DE (2013) A wildfire risk assessment framework for land and resource management. Gen. Tech. Rep. RMRS-GTR-315. Forest Service US Department of Agriculture, Rocky Mountain Research Station
- Seaman J, Hernandez E, Hindi S, Aguilar J (2021) Marshall fire may have destroyed 1,000 homes in Boulder County, officials say. *The Denver Post*. Published December 31, 2021, Retrived January 2022 from <https://www.denverpost.com/2021/12/31/marshall-fire-boulder-county-friday/>
- Srock AF, Charney JJ, Potter BE, Goodrick SL (2018) The hot-dry-windy index: a new fire weather index. *Atmosphere* 9(7):279
- Stavros EN, Iglesias V, Decastro A (2021) The wicked wildfire problem and solution space for detecting and tracking the fires that matter. *Earth Space Sci Open Archive*. <https://doi.org/10.1002/essoar.10506888.1>
- Stocks BJ, Lawson BD, Alexander ME, Van Wagner CE, McAlpine RS, Lynham TJ, Dube DE (1989) The Canadian forest fire danger rating system: an overview. *Forestry Chronicle* 65(5):450–457
- Thomas D, Phillips B, Fothergill A, Blinn-Pike L (2009) Social vulnerability to disasters. CRC Press, Boca Raton, FL
- US Bureau of Labor Statistics. (2021). *Consumer Price Index*. Retrieved January 2022 from <https://www.bls.gov/cpi/>
- US Environmental Protection Agency. (2021). *Research on Health Effects from Air Pollution*. Office of Science Information Management: Washington, D.C. <https://www.epa.gov/air-research/research-health-effects-air-pollution>
- USDA and DOI. (2007). *Wildland Fire Management: The National Fire Plan*. United States Department of Agriculture and United States Department of the Interior: Washington, D.C. <http://www.forestsandrangelands.gov/>
- USGS. (2018). *Fire Danger Forecast*. United States Geological Survey by Land Change Science Program <https://www.usgs.gov/programs/land-change-science-program/science/fire-danger-forecast>
- USHF. (2006). *Healthy forests report: FY 2006 Final Accomplishments*. US Healthy Forests and Rangelands, Retrieved January 2022 from <https://www.forestsandrangelands.gov/resources/reports/index.shtml>
- Venn TJ, Calkin DE (2011) Accommodating non-market values in evaluation of wildfire management in the United States: challenges and opportunities. *Int J Wildland Fire* 20(3):327–339
- Webler T, Tuler S, Dow K, Whitehead J, Kettle N (2016) Design and evaluation of a local analytic-deliberative process for climate adaptation planning. *Int J Justice Sustain* 22(2):166–188. <https://doi.org/10.1080/13549839.2014.930425>
- WH EO. (2016). *White House Executive Order 13728 FACT SHEET: Mitigating the risk of wildfires in the wildland-urban interface*. Retrieved January 2022 from <https://www.whitehouse.gov/the-press-office/2016/05/18/fact-sheet-mitigating-risk-wildfires-wildland-urban-interface>
- Wildfire Technology Funders Group. (2022). The State of FireTech: Progress, Gaps, Futures. *Wonder Labs, California, USA*. [https://www.wonder-labs.org/uploads/6/4/2/1/6421555/stateoffiretech\\_v4\\_3.pdf](https://www.wonder-labs.org/uploads/6/4/2/1/6421555/stateoffiretech_v4_3.pdf)
- Wunder S, Calkin DE, Charlton V, Feder S, de Arano IM, Moore P, y Silva FR, Tacconi L, Vega-García C (2021) Resilient landscapes to prevent catastrophic forest fires: Socioeconomic insights towards a new paradigm. *Forest Policy Econ* 128:102458. <https://doi.org/10.1016/j.forpol.2021.102458>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

## Authors and Affiliations

**Negar Elhami-Khorasani<sup>1</sup>**  · **Hamed Ebrahimian<sup>2</sup>** · **Lawrence Buja<sup>3</sup>** · **Susan L. Cutter<sup>4</sup>** · **Branko Kosovic<sup>5</sup>** · **Neil Lareau<sup>2</sup>** · **Brian J. Meacham<sup>6</sup>** · **Eric Rowell<sup>7</sup>** · **Ertugrul Taciroglu<sup>8</sup>** · **Matthew P. Thompson<sup>9</sup>** · **Adam C. Watts<sup>10</sup>**

<sup>1</sup> University at Buffalo, Buffalo, USA

<sup>2</sup> University of Nevada, Reno, USA

<sup>3</sup> University of Nevada, Reno, USA

<sup>4</sup> University of South Carolina, Columbia, USA

<sup>5</sup> Weather Systems and Assessment Program, National Center for Atmospheric Research, Boulder, USA

<sup>6</sup> Meacham Associates, Shrewsbury, USA

<sup>7</sup> Desert Research Institute, Reno, USA

<sup>8</sup> University of California, Los Angeles, USA

<sup>9</sup> USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO, USA

<sup>10</sup> USDA Forest Service, Pacific Wildland Fire Sciences Laboratory, Seattle, WA, USA